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Determination of Preventive Maintenance Lead Time Using Hybrid Analysis

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Abstract:

The time for conducting Preventive Maintenance (PM) on an asset is often determined using a predefined alarm limit based on trends of a hazard function. In this paper, the authors propose using both hazard and reliability functions to improve the accuracy of the prediction particularly when the failure characteristic of the asset whole life is modelled using different failure distributions for the different stages of the life of the asset. The proposed method is validated using simulations and case studies.

Keywords: Alarm limit, Preventive maintenance, Reliability, Hazard

1. Introduction

Today's industrial practice in asset management requires effective strategies to be developed in the area of Preventive Maintenance (PM). The objective of PM is to maintain an asset above a certain level of reliability and to avoid catastrophic failures using the lowest possible cost. To achieve this objective, PM must be conducted at the right time.

Several factors such as the accuracy of failure prediction and the alarm limit value can affect the determination of the optimum PM time. The function used to determine the PM time is also one of these factors. In the authors' view, the PM time is best predicted using the reliability function $R(t)$ which is the most direct expression to describe the failure properties of systems. The reliability function is sometimes also termed the survivor function [1].

These days, the hazard function is often used to predict when PM should be carried out [2-5]. The hazard function measures the failure rate in a system and is concerned with the probability that a system will fail in the next interval $(t, \Delta t]$ if this system still survives at time *t*. The hazard function is related to the reliability function, but is not equivalent to it. In the authors' view the PM time predicted based on the hazard function needs to be cross-referenced against the reliability function when the failure pattern of a system is composed of several different failure distributions. This paper illustrates this argument through some case studies.

The rest of this paper is organised in the following manner. In section 2, the explicit expression for the hazard function described in a bath basin curve and the corresponding reliability function are derived. In section 3, a suitable method to determine PM time is demonstrated using three examples. Finally, some conclusions and comments are provided in section 4.

2. Hazard Functions and Corresponding Reliability Functions

To illustrate the authors' argument, the explicit expression for hazard functions and corresponding reliability functions should be derived.

Research and industrial experiences have shown that system failures, in terms of hazards, have six common patterns [2]. For simplicity, we choose the bath basin pattern shown in Figure 1 as an example.

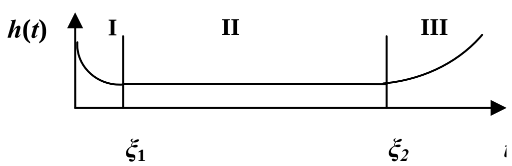


Figure 1. Bath basin failure pattern

The bath basin failure pattern is a typical failure pattern of a mechanical system. It consists of three phases. Phase I represents infant mortality, i.e., the probability of failure declines with age. Phase II represents random failure, i.e., the probability of failure is constant. Phase III represents wear-out, i.e., the probability of failure increases with age. The hazard function of the bath basin failure pattern (a) is given by equation (1) which indicates that in both Phase I and III, the system exhibits Weibull failure distributions with shape parameters $\beta_1<1$ and $\beta_2>1$ respectively. On the other hand, this system has, in Phase II, an exponential failure distribution with a constant failure rate $\lambda = (\beta_1\alpha_1)(\alpha_1\xi_1)^{\beta_1-1}$. Note that equation (1) can be employed to model the remaining five patterns of failures, although these models do not appear to exist at this point time.

$$h(t) = \begin{cases} (\beta_1\alpha_1)(\alpha_1 t)^{\beta_1-1} & 0<t<\xi_1 \quad 0<\beta_1<1 \quad \alpha_1>0 \\ (\beta_1\alpha_1)(\alpha_1\xi_1)^{\beta_1-1} & \xi_1 \le t < \xi_2 \\ (\beta_1\alpha_1)(\alpha_1\xi_1)^{\beta_1-1} + (\beta_2\alpha_2)[\alpha_2(t-\xi_2)]^{\beta_2-1} & t\ge\xi_2 \quad \beta_2>1 \quad \alpha_2>0. \end{cases} \tag{1}$$

The reliability function corresponding to equation (1) can be determined by

$$R(t) = \exp(-\int_0^t h(u)du) \cdot \tag{2}$$

That is:-

$$R(t) = \begin{cases} \exp[-(\alpha_1 t)^{\beta_1}] & 0\le t<\xi_1 \quad 0<\beta_1<1 \quad \alpha_1>0 \\ \exp[-(\beta_1\alpha_1)(\alpha_1\xi_1)^{\beta_1-1}(t-\xi_1+\frac{\xi_1}{\beta_1})] & \xi_1 \le t<\xi_2 \\ \exp\{-(\beta_1\alpha_1)(\alpha_1\xi_1)^{\beta_1-1}(t-\xi_1+\frac{\xi_1}{\beta_1})-[\alpha_2(t-\xi_2)]^{\beta_2}\} & t\ge\xi_2 \quad \beta_2>1 \quad \alpha_2>0. \end{cases} \tag{3}$$

Hazard functions and reliability functions can be derived from each other. However, a system that has a low hazard rate cannot guarantee that it has high reliability. This argument can be illustrated using the following cases.

3. Cases

The following two cases are considered:

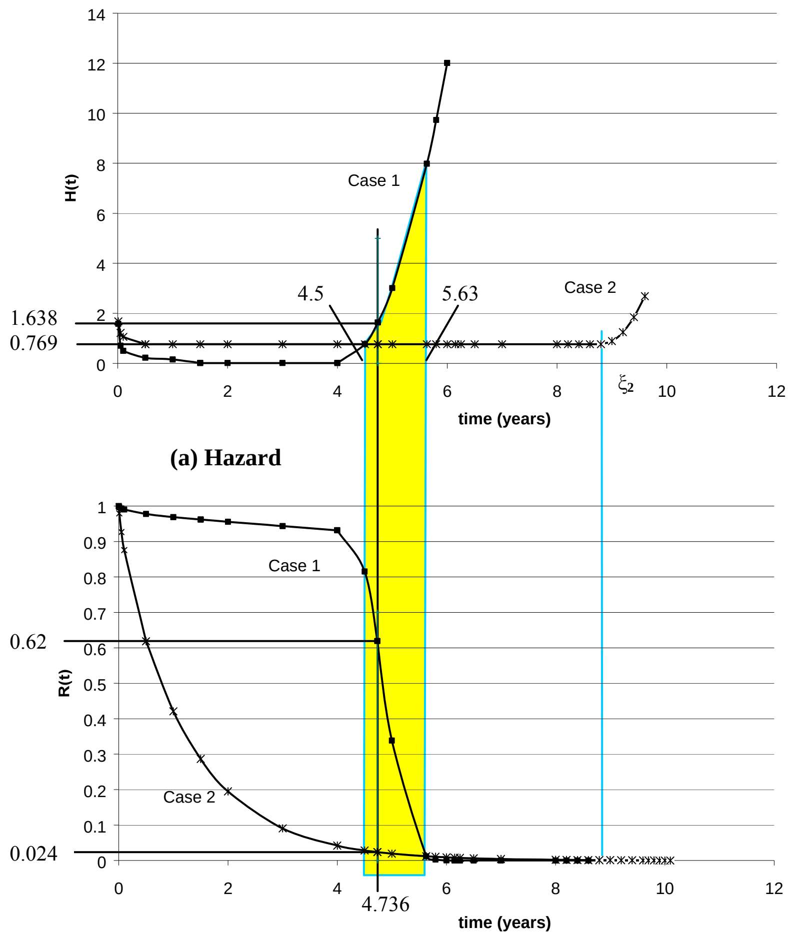
Case1: α_1=0.8 */year*, α_2=1 */year*, β_1=0.5, β_2=3, ξ_1=1.5 *years* and ξ_2=4 *years*

Case 2: α_1=0.8 */year*, α_2=1 */year*, β_1=0.8, β_2=3, ξ_1=0.5 *years* and ξ_2=8.8 *years*

Substituting the above parameters into equation (1) and equation (3) respectively, the changes to both the hazard and the corresponding reliability can be demonstrated in Figure 2 (a, b).

Figure 2 shows that both the hazard and reliability of Case 1 are higher than Case 2 between 4.5 years and 5.63 years. If the critical limit for the hazard is set to be 1.638, then when the hazard of Case 1 reaches this level, the hazard of Case 2 is only 0.769. It seems that the hazard of Case 2 lies below the alarm limit. However, the reliability of Case 1 at that point is 0.62, whereas the reliability of Case 2 is 0.024, much lower than that of Case 1. This indicates that in some cases reducing the hazard does not guarantee an increase in reliability.

Currently, two major methods are used to predict PM time based on hazard functions. The first method establishes a hazard alarm limit in advance. The time when a hazard of an asset reaches this alarm limit is regarded as the time for PM [3]. The second method takes the time when the hazard function curve shows the wear-out phase of its life cycle as the PM time [2]. According to the above analysis, it is shown from the first method that using a predefined alarm limit to predict PM time based on the hazard function can be misleading in some cases.



(a) Hazard

(b) Reliability

Figure 2. Hazard curves (a) and the corresponding reliability curves (b)

If the second method to predict PM time using the hazard function is employed, i.e., ξ_2 of about 8.8 years is chosen as an alarm time for PM, it can be found that the reliability of Case 2 is lower than 0.01 at time ξ_2. In this situation, choosing time ξ_2 as the PM time is certainly inappropriate because the probability of system failure well before the alarm time is very high.

The above analysis method can also be used to study cases where the failure distributions of systems are non-Weibull. For example, in the case given by Jardine [3], the hazard function was derived based on the proportional hazard model using historical oil monitoring and maintenance data of mine haul truck wheel motors. It was:-

$$h(t) = \frac{2.891}{23360}\left(\frac{t}{23360}\right)^{1.891} e^{z(t)}, \tag{4}$$

where, $z(t)$ is the composite covariate which is composed of significant covariates (here they are the values of different particles in oil) and their associated weights. For application convenience, the hazard control limit was converted into a composite covariate control limit curve shown in Figure 3. If the following covariate function $z(t)$ is used to simulate the monitored composite covariate of a wheel motor, i.e.,

$$z(t) = \begin{cases} 0.1 & 0 < t \le 10^4 \quad hours \\ 0.1 + \dfrac{1}{1.48745 \times 10^{11}}(t^{2.891} - 10^{11.564}) & t > 10^4 \quad hours \end{cases}, \tag{5}$$

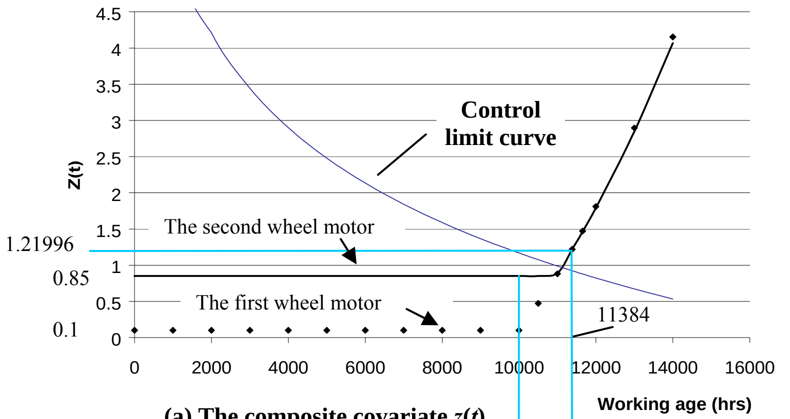
then the hazard function of this wheel motor is given by

$$h(t)=\begin{cases}\frac{2.891}{23360}(\frac{t}{23360})^{1.891}e^{0.1} & 0<t\le 10^4 \ hours \\ \frac{2.891}{23360}(\frac{t}{23360})^{1.891}\exp[0.1+\frac{1}{1.48745\times 10^{11}}(t^{2.891}-10^{11.564})] & t>10^4 \ hours\end{cases}. \quad (6)$$

According to equation (2), the reliability function of this wheel motor can be found to be

$$R(t)=\begin{cases}\exp(-\frac{e^{0.1}t^{2.891}}{23360^{2.891}}) & 0<t\le 10^4 \ hours \\ \exp\{-\frac{e^{0.1}}{23360^{2.891}}[10^{11.564}+\frac{1.48745\times 10^{11}}{e^{2.463527}}(\exp(\frac{t^{2.891}}{1.48745\times 10^{11}})-e^{2.463527}) & \\ & t>10^4 \ hours\end{cases} \quad (7)$$

Figure 3 shows the changes of the composite covariate $z(t)$ and the reliability of the wheel motor (the first wheel motor). From Figure 3 (a), it can be found that the composite covariate $z(t)$ had exceeded its control limit (1.21996) in the inspection at working age t=11384 hours. This wheel motor was recommended to be replaced immediately. Figure 3 (b) indicates that the reliability of this wheel motor at that moment (t=11384 hours) is 0.84. In addition, it can also be seen from Figure 3 that the reliability of the wheel motor fell under 0.91 (0.909) when its composite covariate started to increase at the age of 10000 hours. Furthermore, in order to make a comparison, we supposed that the composite covariate of another wheel motor is represented by the solid-line in Figure 3 (a). This wheel motor is denoted as the second wheel motor in order to distinguish it from the wheel motor mentioned above (the first wheel motor). It can be found from Figure 3 (b) that the reliability of the second wheel motor is much lower than the first between 8000 hours and 12000 hours. According to the control limit curve, both wheel motors are recommended to be replaced at the same working age



(a) The composite covariate *z*(*t*)

(b) The reliability of the wheel motor

Figure 3. The composite covariate *z*(*t*) (a) and the reliability of the wheel motor (b)

(11384 hours). However, the reliability of the second wheel motor is 0.74 at that moment, much lower than the reliability of the first at the same time (0.84). The solid-line in Figure 3 (b) demonstrates that the reliability of the second wheel motor has fallen under 0.84 at working age=10000 hours (0.817). Therefore, if the reliability of the second wheel motor is to be maintained above 0.84, it should be replaced before 10000 hours, 1384 hours earlier than the replacement time suggested by the composite covariate limit curve.

A system often has different hazard functions under different operation conditions. An example is shown in Figure 4 which was obtained using a bearing test rig. The test rig was composed of a shaft with a wheel and two ball bearings. The shaft was driven by a motor through a pair of flexible couplings. The left bearing housing is designed to move in two opposite directions to simulate the different degrees of misalignment of the shaft. The hazard of the right bearing shown in Figure 4 was determined under two conditions: misalignment of the shaft at 0.5 mm and a well aligned shaft.

A shaft speed of 960 rpm was chosen with an operation load of 0.89 kW. Both bearings were in healthy condition during the experiments. An accelerometer was mounted on the right bearing housing to detect the vibration signal of the bearing. The sampling frequency for data acquisition was 10kHz. In each test, 20,000 samples of data were collected.

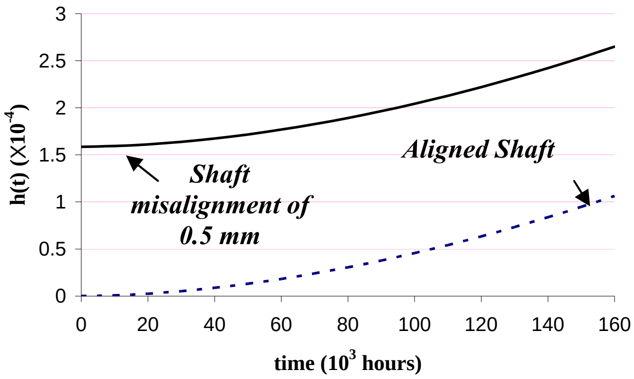


Figure 4. Hazard of the right bearing

Figure 5 shows the reliability of the test bearing corresponding to Figure 4. From Figure 4, it can be seen that a common hazard alarm limit cannot be predefined for the test bearing under two different conditions. The initial hazard of the bearing under the first condition was higher than the hazard at 160,000 hours of the bearing under the second condition. Figure 5 indicates that at 160,000 hours, the failure probability of the bearing under the second condition was almost 100%. In this case, only the reliability function can be used to determine the time for conducting PM. For example, if the predefined reliability limit is 90%, then the PM time for the bearing under the first condition was 664 hours whereas for the bearing under the second condition was 37,600 hours.

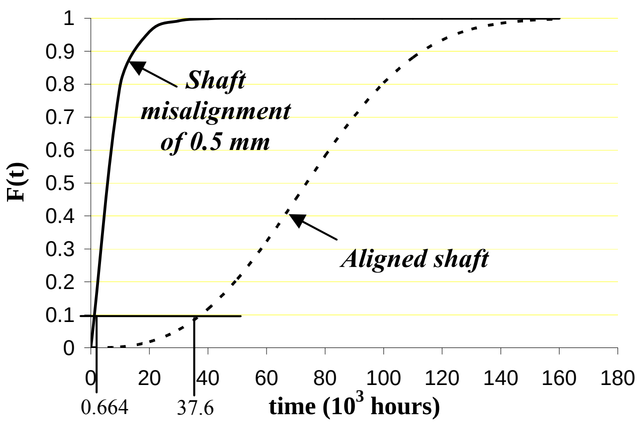


Figure 5. Failure distribution of the right bearing

4. Conclusions and comments

Using the hazard function to make PM decision is not suitable for those failure patterns which represents the failure characteristics of an asset at different stages using several different failure distributions. Resulting PM decisions based on the hazard rate may not be an accurate reflection of the reliability of assets. The PM time predicted based on the hazard function should therefore be cross referenced against corresponding reliability functions.

5. References

1. Cox, D.R., and Oakes, D., *Analysis of Survival Data*. 1984, London: Chapman & Hall. 91-113.
2. Moubray, J., *Reliability Centred Maintenance*. 2nd ed. 1997, New York: Industrial Press.
3. Jardine, A.K.S., and Banjevic, D, *Optimizing a mine haul truck wheel motors' condition monitoring program.* J. of Quality in Maintenance Engineering, 2001. **7**(4): p. 1355-2511.
4. Dubi, A., *Analytic approach & Monte Carlo methods for realistic systems analysis.* Mathematics and Computers in Simulation, 1998. **47**(3): p. 243-269.
5. Wang, K.S., Po, H.J., Hsu, F.S., and Liu, C.S., *Analysis of equivalent dynamic reliability with repairs under partial information.* Reliability Engineering & System Safety, 2002. **76**(1): p. 29-42.